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A COMPARISON BETWEEN RADIAL AND NON-RADIAL DATA ENVELOPMENT ANALYSIS (DEA) MODELS: A CASE OF TRAWL VESSELS IN MALAYSIA COASTAL SEAS

(*Perbandingan antara Model Analisis Penyampulan Data (APD) Jejari dan Bukan Jejari: Satu Kes Vesel Pukat Tunda di Laut Pantai Malaysia)*

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ABSTRACT

In Malaysia, the consumption of fish-based protein is becoming increasingly popular in line with the growing population. However, the mismatch between fish production and the high demand for fish has led to the categorization of the fishing industry in Malaysia as inefficient and in a critical state. Among the factors contributing to this inefficiency are overfishing and the use of destructive vessels such as trawlers. In this study, the objective is to find the efficiency of trawlers for fishing was assessed in 12 coastal areas in Malaysia using two basic approaches with very different characteristics known as radial and non-radial Data Envelopment Analysis (DEA) models. The radial model is represented by the Charnes, Cooper, and Rhodes (CCR) model and the Banker, Charnes, and Cooper (BCC) model while the non-radial model is denoted by the Slack-Based Measure (SBM) model. Furthermore, a comparison of efficiency scores among the models was conducted to assess consistency between them. The Spearman's Rank Correlation test revealed that the CCR and SBM models were significantly highly correlated. This shows that there is no significant difference between the radial model and the non-radial model for this case. The study found that the most efficient Decision-Making Unit (DMU) was Pulau Pinang, while the least efficient DMU was Johor Timur.

Keywords: radial model; non-radial model; consistency; trawlers

ABSTRAK

Di Malaysia, pengambilan protein berasaskan ikan semakin popular seiring dengan pertambahan populasi. Bagaimanapun, ketidakpadanan antara pengeluaran ikan dengan permintaan yang tinggi terhadap ikan telah menyebabkan industri perikanan di Malaysia dikategorikan sebagai tidak cekap dan berada dalam keadaan kritikal. Antara faktor yang menyumbang kepada ketidakcekapan ini ialah penangkapan ikan yang berlebihan dan penggunaan kapal pemusnah seperti pukat tunda. Dalam kajian ini, objektif nya adalah untuk mengukur kecekapan pukat tunda untuk menangkap ikan telah dinilai di 12 kawasan pantai di Malaysia menggunakan dua pendekatan asas dengan ciri-ciri yang sangat berbeza dikenali sebagai model Analisis Penyampulan Data (DEA) jejari dan bukan jejari. Model jejari diwakili oleh model *Charnes*, *Cooper*, dan *Rhodes* (CCR) dan model *Banker*, *Charnes*, dan *Cooper* (BCC) manakala model bukan jejari dilambangkan dengan model *Slack-Based Measure* (SBM). Seterusnya, perbandingan skor kecekapan diantara model dikira untuk melihat keseragaman diantara model. Ujian Korelasi Pangkat Spearman mendedahkan bahawa model CCR dan SBM mempunyai korelasi tinggi yang signifikan. Ini menunjukkan bahawa tidak terdapat perbezaan yang signifikan antara model jejari dan model bukan jejari bagi kes ini. Kajian mendapati Unit Pembuat Keputusan (DMU) paling cekap ialah Pulau Pinang, manakala DMU paling kurang cekap ialah Johor Timur.

Kata kunci: model jejari; model bukan jejari; keseragaman; pukat tunda

1. Introduction

Malaysia is one of the strategic countries in Southeast Asia because geographically, Malaysia is surrounded by four different seas: the South China Sea, the Sulu Sea, the Sulawesi Sea, and the Strait of Malacca. This makes Malaysia one of the main routes for the global trade industry (Department of Fishery Malaysia 2022). Malaysia also has a coastal area with a total length of 3773 kilometers, making Malaysia a significant contributor to the fisheries sector.

Over time, the population of Malaysia has been increasing, and the demand for protein-based raw materials such as fish has also risen. The mismatch between fish production and the high demand for fish has led to the categorization of the fishing industry in Malaysia as inefficient and in a critical state. According to the Department of Fisheries Malaysia in the National Fisheries Development Plan (2021-2030), Malaysia's fishery resource stocks are declining with the remaining stock density biomass at 15% from the original biomass, totaling 150,710 metric tons in the 1970s. Meanwhile, according to the Food and Agriculture Organization (FAO), sustainable biomass nowadays should be at the level of 40 to 60%.

The main factors contributing to this problem are overfishing and the use of destructive fishing equipment. One of them is the use of fishing equipment such as trawl vessel, which not only destroy the seabed and fish habitats but also catch trash fish, the species that should not be catch as the species play a large and very vital role in keeping the underwater ecosystem balanced and thriving (Harley 2015). This causes the size of the fish catch to decrease over time, forcing fishermen to spend more time at sea to ensure economic returns. Additionally, external factors such as uncontrolled coastal area development also contribute to the annual decline of the country's fishery resources.

Research from the Department of Fisheries Malaysia also recorded that 60% of sea catches using trawl vessel consist of fish meal, including fish species with high commercial value such as red snapper, seabream, threadfin bream, croaker, grouper, squid, and crab. If the population of these species is allowed to grow, it can provide significant yields to fishermen and serve as fishery resources with high economic value. Therefore, it is crucial to evaluate the technical efficiency performance of trawl vessels carefully to develop the best approach and to reduce the negative impact on the dwindling fishery resources.

However, the use of destructive equipment such as bombs, cyanide, and double-boat trawlers has been banned through the enactment of the Fisheries Act 1985 (Abdullah 2016). Nevertheless, the use of trawl vessels, undeniably a major contributor to fishery landings, is still permitted. At the same time, the recommendation to reduce these vessels by switching to other vessels is being actively introduced by the Department of Fisheries Malaysia. Based on the statistical data of the Department of Fisheries Malaysia, it is found that trawl net equipment across all zones is the main contributor to the country's marine fish catch, around 46% (726,400 tons) in 2016 (Mohd Nawi 2018).

The main objective of this study is to examine the efficiency of trawl vessels in Malaysian coastal waters using the radial and non-radial models and to identify the consistency of the models used in measuring the efficiency scores of trawl vessels in Malaysian coastal waters. Radial models assume proportional change of inputs or outputs and usually disregard the existence of slacks in the efficiency scores. A non-radial model by the name of slacks-based measure (SBM) was developed by Tone (2001) which deals with slacks directly and measures the full range of slack variables and their shortcomings in efficiency assessment which is a shortcoming of the radial models (Tone 2001).

2. Methodology

Data Envelopment Analysis (DEA) is generally a method for determining the relative efficiency of a decision-making unit (DMU). The DMU used in this study is the use of trawl vessels in coastal waters of Malaysia. Efficiency in DEA means the output goal that needs to be achieved with the minimum use of input resources (Dagang 2016).

This DEA method was initially introduced by Farrel in 1957 (Førsund & Sarafoglou 2002). Then in 1978, this method was explored and developed further by Charnes, Cooper, and Rhodes by assuming that the production of an organization involves inputs and outputs. A study by Førsund and Sarafoglou (2002) discussed in more detail the relationship between the model initially explored by Charnes, Cooper, and Rhodes in 1978 with the model originally developed by Farrel in 1957. The initial DEA approach introduced by Charnes, Cooper, and Rhodes is known as the CCR (Charnes, Cooper, and Rhodes) model, which is an input-oriented model assuming constant returns to scale (CRS). However, subsequently, many researchers proposed new alternatives to the assumption, such as Färe *et al.* (1983) and Banker *et al.* (1984), who suggested the variable returns to scale (VRS) model.

Then in 2001, the Slack-Based Measure (SBM) model was introduced by Tone (2001), where the scale measurement of this model considers input excess and output shortfall in the efficiency score calculation for a DMU. Input excess and output shortfall are known as slack variables (Tone 2001). The SBM model is also called a non-radial model because it does not assume proportional changes in inputs and outputs to obtain the maximum reduction rate in inputs, which might discard various parts of the original input resources. Therefore, this model can differentiate between efficient and inefficient DMUs. If the slack variable value is zero, it means the DMU is efficient and vice versa. If a DMU is inefficient, the input excess and output shortfall values can be basic references for improving the DMU besides examining external factors of the DMU's inefficiency (Ibrahim & Ismail 2022). Meanwhile, the radial model can only classify efficient and inefficient models without knowing the value of input excess and output shortfall for a DMU. This is because the radial model ignores the slack variables in the efficiency score calculation. The radial models in the DEA method are the CCR and BCC models. The term "radial efficiency" means that the proportional reduction of inputs or proportional increase of outputs is the main cause in measuring and evaluating the efficiency of a DMU. In brief, the radial model allows for modifying all inputs or all outputs per DMU unit proportionally without knowing the value of input excess and output shortfall for a DMU.

In DEA method, the most important step in measuring efficiency is the selection of appropriate inputs and outputs. This is because the chosen inputs and outputs must align with the study's objectives and have sufficient data. Insufficient data will prevent the achievement of the objective to determine the efficiency of a particular DMU. Additionally, in this study, the determination of inputs and outputs is based on the variables or inputs and outputs used in previous studies, as well as the availability of data in the 2022 Fisheries Statistics Book published by the Malaysian Department of Fisheries. The studies by Rais *et al.* (2019) and Abdullah *et al.* (2024) were used as references to determine both input and output. This is because the inputs and output used align with the classification by the Malaysian Department of Fisheries. The inputs used are the number of fishing days, the number of trawler vessel fishermen, and the number of licensed trawler vessels in the coastal waters of Malaysia. While, the output is the total fish landings.

Furthermore, this study will use an input-oriented DEA model or input control, because according to Sangün *et al.* (2018), controlling inputs in the fisheries sector is easier compared to controlling outputs due to the presence of many unpredictable variables in the outputs. Input-oriented models means a models where DMUs are deemed to produce a given amount of outputs with the smallest possible amount of inputs (inputs are controllable) while vice versa for output-oriented model (Huguenin 2012).

In this study, after obtaining efficiency scores using three different models, namely the CCR, BCC, and SBM models, these models will be compared and analyzed using correlation analysis to identify the consistency between models. Consistency here means that the relationship between the two models is high, where the efficiency scores between the two models are not much different. Correlation analysis is used because it is a statistical technique used to investigate the magnitude and significance of the relationship (Prematunga 2012).

2.1. *Input-oriented CCR model*

The input-oriented CCR model used in this study is shown in Eq. (1) below, where it is assumed that there are n DMUs being used, k is the current DMU being evaluated, and the j-th DMU produces s outputs $(y_{rj}, \dots, y_{sj})$ using m inputs $(x_{ij}, \dots, x_{mj})$.. Next, ϕ represents the efficiency score of the k-th DMU, and λ_j represents the dual variable that identifies the composite of a DMU for the inefficient j-th DMU. A DMU is called efficient when $\phi = 1$. The relative efficiency of the k-th DMU is shown as below (Cooper *et al.* 2006).

$$\text{Min } \phi \tag{1}$$

subject to

$$\sum_{j=1}^{n} \lambda_j Y_{ij} \leq Y_{ik} \quad r = 1,2, \dots, s;$$

$$\sum_{j=1}^{n} \lambda_j X_{rj} \geq \phi X_{rk} \quad i = 1,2, \dots, m;$$

$$\lambda_j \geq 0 \qquad j = 1,2, \dots, n;$$

where,

ϕ = Score Effieciency for a DMU
j = The analyzed DMU
m = Total Input
s = Total Output
n = Number of DMUs
i = Number of Input
r = Number of Output
λ_j= Dual Variable

2.2. *Input-oriented BCC model*

Meanwhile, the input-oriented BCC model used in this study is the model introduced by Banker *et al.* (1984). This model allows for variable returns to scale to estimate the pure technical efficiency of a DMU by referring to the efficient frontier. These returns can be increasing, decreasing, or constant according to the scale for a DMU. The BCC model has the same structure as the CCR model with the addition of one constraint, which is:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2}$$

This constraint causes the objectives of the two models to differ. The CCR model is used to measure overall technical efficiency, while the BCC model is used not only to measure overall technical efficiency but also to measure pure technical efficiency and scale efficiency. This constraint also assumes positive dual variables in the optimal solution (Dagang 2016). Additionally, the BCC model was introduced to address the issue that the assumption of constant returns to scale may not be appropriate in some real-life situations (Cheng & Ismail 2022)

2.3. *Input-oriented SBM model*

Lastly, the non-radial model, the input-oriented SBM model constructed by Tone (2001), is shown in the Eq. (3) below (Cooper *et al.* 2006):

$$\tau = \text{Min}_{\lambda, s^-, s^+}\ 1 - \frac{1}{m}\sum_{i=1}^{m} \frac{\hat{s}_i^-}{x_{ik}} \tag{3}$$

subject to

$$X_{ik} = \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- \qquad i = 1,2,\dots,m;$$

$$Y_{rk} = \sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ \qquad r = 1,2,\dots,s;$$

$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0 \qquad j = 1,2,\dots,n\ ;$$

where,

τ = Input-oriented SBM efficiency score
j = The analyzed DMU
m = Total Input
s = Total Output
n = Number of DMUs
i = Number of Output
r = Number of Intput
λ_j = Dual Variable
s_i^- = Input Slack Variable
s_r^+ = Output Slack Variable

It is assumed that there are n DMUs being used, k is the current DMU being evaluated, and the j -th DMU produces s outputs $(y_{rj}, \dots, y_{sj})$ using m inputs $(x_{ij}, \dots, x_{mj})$. Next, τ represents the efficiency score of the k-th DMU, and λ_j represents the dual variable that identifies the composite of a DMU for the inefficient j-th DMU. Meanwhile, s_r^+ is the input excess value, and s_i^- is the output shortfall value.

2.4. *Spearman's rank correlation test*

The Spearman's rank correlation test, ρ is a non-parametric technique used to measure the strength and direction of the relationship for a variable or model. The variables used for this correlation test must be ordinal or continuous data that have failed the assumptions required to perform the Pearson correlation test (Fikratunnaza 2021). The benefit of using Spearman correlation in ranking is that it is not affected by population distribution. Additionally, this approach involving ranked data tends to be insensitive to outliers and does not require the condition that the collected data must be in frequent intervals. Furthermore, it is suitable for use with small samples and is easy to apply.

In this study, the Spearman's rank correlation matrix test, ρ and the significant value, p are calculated between the CCR, BCC, and SBM models to observe uniformity between the models. The correlation coefficient, ρ will provide information about the relationship between two models, while the p-value will provide information about the significance of the relationship between the models.

Next, this test will measure all relationships between the models (i.e., CCR-BCC, CCR-SBM, BCC-SBM) and compare the Spearman's rank correlation values, ρ between the models for each DMU. For example, if the obtained value has a high correlation, and the p-value is less than 0.05, it can be concluded that the efficiency values between the models are uniform. This test will be conducted using Microsoft Excel software, where the p-value is calculated using the ANOVA test, while the correlation coefficient, ρ is calculated using the equation below:

$$\rho = 1 - \frac{6\sum {d_i}^2}{n(n^2-1)} \tag{4}$$

where,

ρ = Correlation Coefficient
d_i = Diffrence
n = Number of Samples
i = Current sample (i.e. i = 1,2, ... ,12)

The correlation coefficient scale, ρ can be positive or negative. This value has its own meaning, which is to measure the strength and direction of the relationship between two variables (Turney 2023). When the value of ρ is positive, the relationship between the models is positive. Conversely, if the obtained ρ value is negative, it indicates a negative relationship between the models. However, if the value of ρ is 0, this means there is no correlation between the models. For example, ρ = 0.1 indicates a weak positive relationship, while ρ = 0.8 indicates a strong positive relationship. The correlation coefficient scale and interpretation of the strength of the relationship are shown in Table 1 below:

Table 1: Correlation coefficient scale and interpretation (Yan *et al*. 2019)

Correlation Coefficient Scale	Interpretation
$\rho = 0$	No correlation
$0 < \|\rho\| \leq 0.19$	Very weak correlation
$0.2 < \|\rho\| \leq 0.39$	Weak correlation
$0.4 < \|\rho\| \leq 0.59$	Moderate correlation
$0.6 < \|\rho\| \leq 0.79$	Strong correlation
$0.8 < \|\rho\| < 1.0$	Very strong correlation
$\rho = 1$	Monotonic correlation

3. Results

The division of fishing in Malaysia is divided into two: in shore and deep sea. However, the scope of this study is only focused on the use of trawl vessels in Malaysian coastal waters, in shore, covering waters under 30 nautical miles and divided into three zones: A, B, and C (Department of Fishery Malaysia 2022). The coastal waters of Malaysia involved include those on the West Coast, namely Perlis, Kedah, Penang, Perak, Selangor, and West Johor. And at the East Coast include Kelantan, Terengganu, Pahang, and East Johor. Meanwhile, the coastal waters in Malaysian Borneo also include which Sarawak and Sabah. However, Melaka and Negeri Sembilan are not included in the scope of this study as they do not have trawl vessels.

3.1. *Efficiency analysis*

The input and output data for this study were obtained from the Fisheries Statistics Report 2022 published by the Department of Fishery Malaysia (2023). The inputs used in this study are the number of fishing days, the number of trawl vessel fishermen, and the number of licensed fish trawl vessels. The output used is fish landings (in metric tons). By using Excel-Solver software, the efficiency scores for each DMU studied were obtained for each CCR, BCC, and SBM model. Subsequently, the efficiency scores and rank positions for each model were compared to observe their consistency.

Based on a rough observation, the efficiency scores and rank positions for each CCR, BCC, and SBM model were sometimes the same and sometimes different. For example, according to Table 2, the most efficient DMU for each CCR, BCC, and SBM model is Pulau Pinang, with an efficiency score of one and a rank of first. However, the least efficient DMU, which is East Johor, has the same rank of 12 for each model but different efficiency scores: 0.1625 using the CCR model, 0.3988 using the BCC model, and 0.1312 using the SBM model.

Based on the table above, the BCC model indicates that more than 80% of the DMUs studied are efficient. In contrast, the average efficiency scores based on the CCR model and SBM model respectively show that 60% and 54% of the DMUs studied, are efficient. Overall, the average percentage indicates that the efficiency score in Malaysia is above 50% using the three different models. But if we look the score precisely, we can see the ratio of DMU that is inefficient is more or equal to efficient DMU when using CCR and SBM model. Except for BCC model, the score demonstrates that the fisheries sector for each coastal waters in Malaysia is generally efficient, but there is still room for improvement over time.

Table 2: Comparison of efficiency scores for CCR, BCC, and SBM model

DMUs	Score (CCR)	Rank	Score (BCC)	Rank	Score (SBM)	Rank
Perlis	1	2	1	3	1	2
Kedah	1	3	1	2	1	3
Pulau Pinang	1	1	1	1	1	1
Perak	0.2754	11	1	4	0.2742	10
Selangor	0.4587	7	0.9992	5	0.3992	7
West Johor	0.3996	8	0.6992	10	0.3485	8
Kelantan	0.9074	4	0.9678	6	0.7738	4
Terengganu	0.7476	5	0.7747	9	0.5224	5
Pahang	0.3296	9	0.4935	11	0.3002	9
East Johor	0.1625	12	0.3988	12	0.1312	12
Sarawak	0.5916	6	0.8165	8	0.5071	6
Sabah	0.2818	10	0.9495	7	0.2643	11
Average	0.5962		0.8416		0.5434	

These inefficient DMUs can be efficient by doing projection method. This means the efficient DMU can be a benchmarking to inefficient DMUs to be more efficient. In the Table 2, rank is referring to the position of the most efficient DMU, which has an efficiency score of one and is most frequently used as a benchmark or reference for inefficient DMUs. This reference set is derived from the dual variable, λ, from Eq. (1)-(3). A dual variable, λ, value greater than zero means that the less efficient DMU will refer to the more efficient DMU. For this Input-oriented model, each input will be proposed for projection or improvement by reducing the usage of each input while maintaining the same level of output production for each DEA model used. This projection method is not discussing further as not part of this study's objective.

3.2. *Consistency test between models*

This correlation test is calculated using Eq. (4) to obtain the Spearman's rank correlation coefficient, ρ for each model. The significance value, p is obtained from an ANOVA test using Microsoft Excel. The correlation between the models can be visualized through the scatter plots in Figures 1, 2, and 3. While, the Spearman's correlation coefficient, ρ and p-values between CCR-BCC model, CCR-SBM model and BCC-SBM model is show in Table 3 below.

Table 3: Shows the Spearman's correlation coefficient, ρ and p-values between CCR, BCC, SBM model

	CCR model and BCC model	CCR model and SBM model	BCC model and SBM model
Spearman's Rank Correlation Coefficient, $\boldsymbol{\rho}$	0.5771	0.9929	0.6094
$\boldsymbol{p}$-value, $\boldsymbol{p}$	5.19×10^{-2}	4.0×10^{-8}	3.85×10^{-2}

Based on Table 3 above, the correlation value between the CCR model and the BCC model is 0.5771, which is considered moderate and not significant ($p > 0.05$). This indicates that the

CCR and BCC models are not consistent with each other. In other words, the efficiency scores between these two models are differ. The visualization through scatter plot in Figure 1 below proof that the score between model CCR and BCC are not linear with positive trendline. On the other hand, for the CCR and SBM models, the correlation is very high at 0.9929 with a significant p-value $p < 0.05$). This shows that the CCR and SBM models are consistent with each other. Therefore, it is not surprising that the comparison of scores between these two models is quite similar. This means that either model can be chosen to measure efficiency in this sector as the results are comparable. Figure 2 show that both data are linear to each other. Finally, for the BCC and SBM models, the correlation is high with a significant *p*-value $p < 0.05$), indicating that the BCC and SBM models are also consistent with each other. Figure 3 shows that some of data for both models are likely same, and linear.

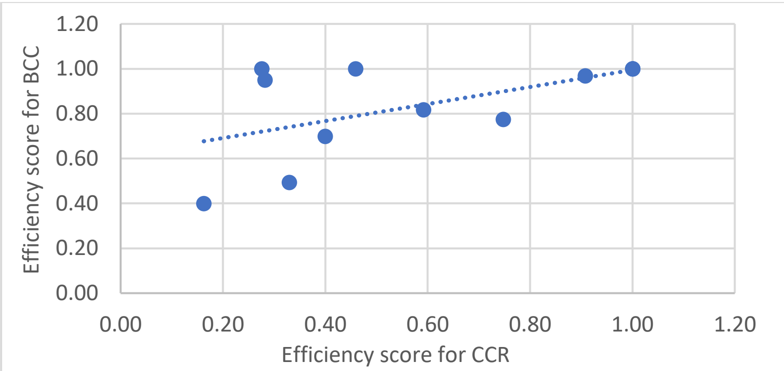

Figure 1: Scatter plot for CCR model and BCC model

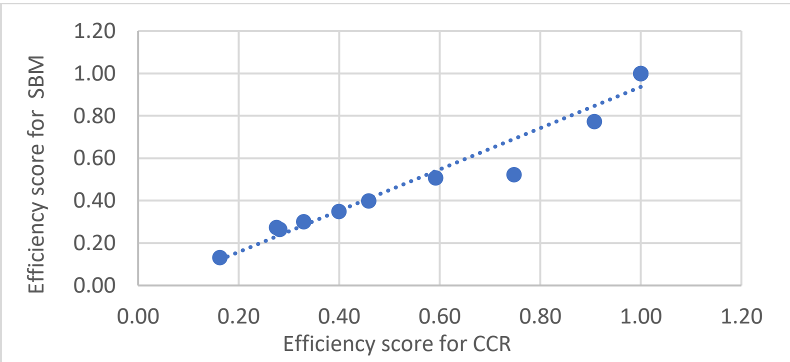

Figure 2: Scatter plot for CCR model and SBM model

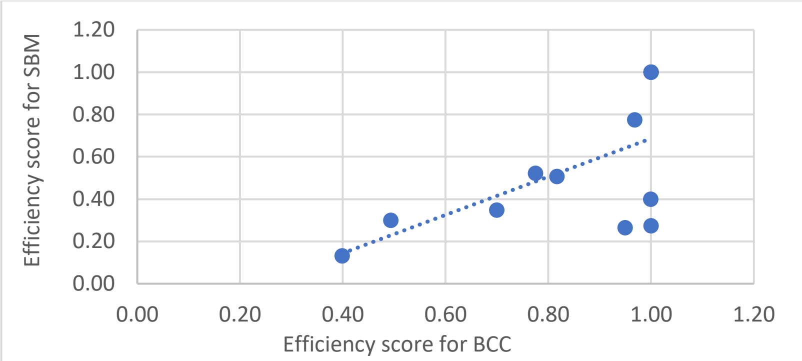

Figure 3: Scatter plot for BCC model and SBM model

4. Conclusions

The purpose of this study are to determine the efficiency score of trawl vessel in Malaysian coastal waters and to compare the consistency among the radial models, which consist of the CCR and BCC models, and the non-radial model, which is the SBM model for measuring the efficiency of the use of fish trawl vessels in 2022. Firstly, the results based on the CCR model show that Perlis, Kedah, and Penang are efficient DMUs, while the BCC model indicates that Perlis, Kedah, Penang, and Perak are efficient DMUs with score one. Both models show that Penang is the most efficient DMU with score 1 and the DMU frequently used as a reference by other coastal waters to become efficient and East Johor is the least efficient DMU, with an average efficiency score of 0.2308 from the three models. The researcher then used the non-radial SBM model to measure the efficiency of trawl vessels in the Malaysian coastal waters. The analysis results show that the efficient DMUs using the SBM model are the same as those identified by the CCR model: Perlis, Kedah, and Penang. The SBM model also indicates that Penang is the most efficient DMU and Johor Timur is the least efficient DMU.

Subsequently, the analysis compared the models CCR-BCC, CCR-SBM, and BCC-SBM to identify consistency among the models. The comparison results show that the CCR-SBM model is the most consistent, as it has the highest correlation value among the models. Therefore, a choice between the CCR model and the SBM model can be made since both models are consistent and produce similar efficiency scores. In contrast, the model that is not consistent is the CCR-BCC model due to the moderate and non-significant correlation between the models. Hence, a choice between these two models cannot be made as they are inconsistent and would produce different efficiency scores. In conclusion, the CCR model and the SBM model are linearly related which shows that a high degree of the relationship between two models.

Besides, according to research data from Fisheries and Aquaculture (2020), Malaysia is among the top ten fish-consuming countries in the world. In fact, Malaysia has achieved a surplus in self-sufficiency in fish supply since 2010. However, the fisheries sub-sector in Malaysia has not yet reached maximum and efficient production efficiency. The findings from this study can help to some extent in recommending improvements in efficiency within this sector by identify which coastal water in Malaysia need to be improve.

However, the scope of this study is limited to trawler vessels, focusing on 12 coastal waters in Malaysia, with efficiency improvements involving only three inputs and one output. The scope of this study could be expanded by focusing on the country's economic growth. This could be done by adding another output, such as fish production in Malaysian Ringgit (RM), as in the studies conducted by Rais *et al.* (2019) and Li *et al.* (2020). However, the proposed focus involves trawler vessels and several other vessels that also contribute to the increase in fish catches in Malaysia.

Additionally, long-term studies are recommended. For example, comparing fishery production before, during, and after the COVID-19 pandemic. Such comparisons are crucial to understanding the impact and determining appropriate strategies for managing marine resources in the future. This type of study should be conducted carefully, in collaboration with fisheries industry experts, marine scientists, and other stakeholders to ensure that the data obtained is accurate and provides a comprehensive view of the state of the fisheries industry before, during, and after COVID-19.

Finally, it is hoped that the further research recommendations for this sector will serve as a foundation for researchers interested in conducting more in-depth studies on efficiency measurement in the country's marine capture fisheries sub-sector.

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